MICROSIMULATION AND ACTIVITY-BASED FORECASTING

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ABSTRACT

This paper provides an overview of the state of the art of microsimulation modeling applied to activity-based travel forecasting. The paper defines what is meant by microsimulation and discusses why microsimulation might be a preferred approach to activity-based forecasting in many applications. The issue of synthesizing and updating characteristics of the population being simulated is addressed in some detail. Examples of various types of microsimulation models which have been developed to date are provided, including microsimulation models of auto ownership, residential mobility, route choice and network performance, as well as activity-based travel forecasting models *per se*. The paper concludes with a discussion of research and development issues associated with the continuing development of operational microsimulation models. These include: further evaluation of population synthesizing and updating methods; determination of appropriate levels of model disaggregation; establishing appropriate linkages between model components; examination of the statistical properties of microsimulation models; and demonstration of the computational feasibility of these very computer-intensive modeling systems.

1. INTRODUCTION

The purpose of this paper is to provide an overview of microsimulation concepts and methods which are applicable to activity-based travel forecasting.

Including this very brief introductory section, the paper is divided into six sections. Section 2 defines the term microsimulation. Section 3 discusses the reasons why microsimulation may prove useful or even necessary for at least some types of activity-based travel forecasting applications. Section 4 discusses a key step in the microsimulation process -- synthesizing and/or updating the attributes of the population or sample of individuals whose behavior is being simulated. Section 5 then briefly presents several microsimulation models drawn from a range of applications, including activity-based travel forecasting. Finally, Section 6 discusses some of the research and development issues and directions associated with improving the operational applicability of microsimulation methods.

2. WHAT IS MICROSIMULATION?

While many current modeling efforts are microsimulation based, the term itself is rarely defined. **Simulation** generally refers to an approach to modeling systems which possess the following two key characteristics.

1. The system is a **dynamic** one, whose behavior must be explicitly modeled over time.
2. The system's behavior is **complex**. In addition to the dynamic nature of the system (which generally in itself introduces complexity) this complexity typically has many possible sources, including:

    (a) complex decision rules for the individual actors within the system;
    (b) many different types of actors interacting in complex ways;
    (c) system processes which are path dependent (i.e., the future system state depends both on the current system state and explicitly on how the system evolves from this current state over time);
    (d) the system is generally an "open" one in which exogenous "forces" operate on the system over time, thereby affecting the internal behavior of the system; and/or
    (e) significant probabilistic elements (uncertainties) exist in the system, with respect to random variations in exogenous inputs to the system and/or the stochastic nature of endogenous processes at work within the system.

    Note that in speaking of complexity, we are not merely referring to the difficulty in dealing with very large models with large datasets defined over many attributes for hundreds if not thousands of zones. Rather, we are referring to the more fundamental notion of the difficulty in estimating likely future system states given the inherently complex nature of the system's behavioral processes.

Given the system's complexity, closed-form analytical representations of the system are generally not possible, in which case numerical, computer-based algorithms are the only feasible method for generating estimates of future system states. Similarly, given the system's path dependencies and openness to time-varying exogenous factors, system equilibrium generally is not achieved, hence rendering equilibrium-based models inappropriate. In the absence of explicit equilibrium conditions, the future state of the system again generally can only be estimated by explicitly tracing the evolutionary path of the system over time, beginning with current known conditions. Such numerical, computer-based models which trace a system's evolution over time are what we generally refer to as simulation models.

Note that conventional four-stage travel demand models most clearly are **not** simulation models under this definition. Conventional four-stage models are static equilibrium models which predict a path-independent future year end state without concern for either the initial (current) system state or the path traveled by the system from the current to the future year state. Thus in adopting a simulation approach to modeling activity and travel behavior, one is explicitly rejecting the conventional static equilibrium view of urban systems in favor of a dynamic representation of such systems -- a very significant

decision, both conceptually and practically.
The prefix “micro” simply indicates that the simulation model is formulated at the disaggregate or micro level of individual decision-making (or other relevant) units such as individual persons, households and vehicles. A full discussion of the relative merits of disaggregate versus more traditional aggregate modeling methods is beyond the scope of this paper.[1] I believe, however, it is fair to say that a broad consensus exists within the activity/travel demand modeling community that disaggregate modeling methods possess considerable advantages over more aggregate approaches (including minimization of model bias, maximization of model statistical efficiency, improved policy sensitivity, and improved model transferability -- and hence usability within forecasting applications), and that they will continue to be the preferred modeling approach for the foreseeable future. With respect to microsimulation, the relevant question is to what extent does microsimulation represent a feasible and useful mechanism for using disaggregate models within various forecasting applications.

To begin to explore the way in which microsimulation can be used to apply an activity-based model in a forecasting context, first consider the well known short-run policy analysis/forecasting procedure known as sample enumeration. In this procedure, a disaggregate behavioral model of some form has been developed (say, for sake of illustration, an activity-based model which predicts the number of out-of-home activities in which a worker will participate either before or after work, along with the location, duration and trip chaining implications associated with these activities). A representative sample of decision-makers (in this case workers) typically exists, since such a sample is generally required for model development. This sample defines all relevant inputs to the model with respect to the attributes of all the individuals in the sample. The short-run impact of various policies which might be expected to affect activity scheduling and trip chaining can then be tested by “implementing” a given policy, and then using the model to compute the response of each individual to this policy (where, in this case, the response may involve some combination of changes in the number, timing, duration and/or location of out-of-home activities). Summing up the responses of the individuals provides an unbiased estimate of the aggregate “system” response to the policy in question.

[1] For elegant and concise discussions of the rationale for disaggregate models see, among others, Mackett [1990] and Goulias and Kitamura [1992, 1996].

Figure 1 very simply summarizes this procedure. This figure can be taken as a very generic representation of a microsimulation process for the case of a short-run forecast, in which all model inputs except those relating to the policy tests of interest are fixed, and hence all that needs to be simulated are the behavioral responses of the sampled decision-makers to the given policy stimuli. Thus, in such cases, "sample enumeration" and "microsimulation" are essentially synonymous, and use of the latter term simply emphasizes the disaggregate, dynamic[2] nature of the model. The majority of activity-based microsimulation models developed to date basically fall into this category of short-run, sample enumeration-based models.

Sample enumeration is a very efficient and effective forecasting method **providing**:

1. a representative sample is available;
2. one is undertaking a **short-run** forecast (so that the sample can be assumed to remain representative over the time frame of the forecast); and
3. the sample is appropriate for testing the policy of interest (i.e., the policy applies in a useful way to the sample in question).

Many forecasting situations, however, violate one or more of these conditions. Perhaps most commonly, one is often interested in forecasting over medium to long time periods, during which time the available sample will clearly become unrepresentative (people will age and even die; workers will change jobs and/or residential locations; new workers with different combinations of attributes will join the labor force; etc.). The question then becomes how to properly "update" the sample in order to maintain its representativeness. In other cases, the sample may not be adequate to test a given policy (e.g., it contains too few observations of a particularly important sub-population for the given policy test). If this is the case, how does one "extend" the sample so that a statistically reliable test of the policy can be performed? Finally, their may be cases in which a suitable sample simply does not exist (e.g., perhaps the model has been transferred from another urban area). In such a case, how does one "generate" or **synthesize** a representative sample?

In all of these cases, microsimulation provides a means of overcoming the limitations of the available sample. In the case of the sample becoming less and less representative over time, Figure 2 presents a simple microsimulation framework in which the sample is explicitly updated over time. The behavior predicted at each point in time is then based on a representative sample for that point in time.

If the original sample is either inadequate or missing altogether, then, as shown in Figure 3, an additional step must be inserted into the model, involving **synthesizing** a representative sample from other available (typically more aggregate) data such as census data.

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[2] In such cases, the dynamics involved are usually quite short-run (e.g., activity scheduling over the course of a day or perhaps at most a week; short-run dynamic adaption to a new set of constraints/opportunities; etc.), particularly relative to the much longer-term demographic and socio-economic dynamics which are discussed immediately below.

The remainder of this paper provides more detailed discussion of issues and methods associated with Figures 2 and 3. The final point to note at this stage of the discussion is that these figures assume that the disaggregate behavioral model is itself a dynamic one which must be stepped through time (and hence its inclusion within the time loop). Many current activity-based models are fairly static in nature (or incorporate very short-run dynamics, as discussed in Footnote 2). In such cases, the behavioral model can be removed from the time loop and executed only once, using the desired future year sample which has been estimated through the microsimulation procedure. In order to keep the discussion as simple as possible, however, as well as to emphasize what I believe is the need for explicitly dynamic models of urban processes, the "fully dynamic" representation of the process as contained in Figures 2 and 3 is generally used as the basis for discussion throughout the rest of the paper.

3. WHY MICROSIMULATE?

As briefly discussed in the previous section, a primary motivation for adopting a microsimulation modeling approach is that it may well be the best (and in some cases perhaps the only) way to generate the detailed inputs required by disaggregate models. The strength of the disaggregate modeling approach is in being able to fix decision-makers within explicit choice contexts with respect to:

1. the salient characteristics of the actors involved;
2. the salient characteristics of the choice context (in terms of the options involved, the constraints faced by the actors, etc.) and
3. any context-specific rules of behavior which may apply.

This inherent strength of the disaggregate approach is clearly compromised if one cannot provide adequately detailed inputs to the model. Such compromises occur in at least two forms. One involves using overly aggregate forecast inputs, resulting in likely aggregation biases in the forecasts. The other involves developing more aggregate models in the first place so as to reduce the need for disaggregate forecast input data, thereby building the aggregation bias into the model itself. I believe that a strong case can be made that a primary reason for the relatively slow diffusion of disaggregate modeling methods into travel demand forecasting practice is due to the difficulty practitioners have in generating the disaggregate forecast inputs required by these methods.[3] As described in the previous section, microsimulation in principle eliminates this problem by explicitly generating the detailed inputs required for each actor being simulated.

A second driving force for using microsimulation relates to the **outputs** required from the activity/travel behavior model. Many emerging road network assignment procedures are themselves microsimulation-based (TRANSIMS[4], DYNASMART[5], INTEGRATION[6], etc.) and hence require quite micro-level

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[3] The only significant disaggregate model used in operational settings today is the disaggregate logit mode choice model. Even in this instance, the number of explanatory socio-economic variables used in the models tends to be relatively limited, presumably due to the input forecasting problem.

[4] Barrett, *et. al.* [1995]

inputs from the travel forecasting model.

A third point is that, despite the obviously large computational requirements of a large microsimulation model, it is quite possible that microsimulation will prove to be a computationally efficient method for dealing with large-scale forecasting problems. It is certainly the case that a “micro” list-based approach to storing large spatial databases is far more efficient than “aggregate” matrix-based approaches. To illustrate this, consider a very simple example in which one might want to keep track of the number of workers by their place of residence, place of work, number of household automobiles and total number of household members. Further assume that there are 1000 traffic zones, three auto ownership levels (e.g., 0, 1, 2+) and five household size categories (e.g., 1, 2, 3, 4, 5+). To save this information in matrix format would require a four-dimensional matrix with a total of $1000 \times 1000 \times 3 \times 5 = 15 \times 10^6$ data items. Also note that a large number of the cells in this matrix will have the value zero, either because they are infeasible (or at least extremely unlikely; e.g., 2+ autos in a one-person household) or because one simply does not observe non-zero values for many cells (as will be the case for many origin-destination (O-D) pairs).

In a list-based approach, one record is created for each worker, with each record containing the worker's residence zone, employment zone, number of household autos and household size. Thus, four data storage locations are required per worker, meaning that as long as there are less than $(15 \times 10^6) \div 4 = 3.75 \times 10^6$ workers in this particular urban area the list-based approach will require less memory (or disk space) than the matrix-based approach to store the same information. Obviously, as the number of worker attributes which need to be stored increases, the relative superiority of the list-based approach increases.

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[5] Mahmassani, *et. al.* [1994] and Hu and Mahmassani [1995].

[6] Van Aerde and Yager [1988a, 1988b].

The advantages of list-based data structures for large-scale spatial applications have been recognized for at least twenty years.[7] "Aggregate" urban simulation models such as NBER[8] and CAM[9], both developed in the 1970's used list-based data structures.[10] The key point to be made here with respect to microsimulation is that once one begins to think in list-based terms, the conceptual leap to microsimulation model designs is a relatively small one. Or, turning it around, if one takes a microsimulation approach to model design, efficient list-based data structures quickly emerge as the "natural" way for storing information.

Whether microsimulation possesses other inherent computational advantages relative to more aggregate methods is less clear. Certainly one can advance the proposition that by working at the micro level of the individual decision-maker, relatively simple, clear and computationally efficient models of process can generally be developed. Whether this efficiency in computing each actor's activities translates into overall computation time savings relative to other approaches given the large number of actors being simulated remains to be seen.

A fourth argument in favor of microsimulation is that it raises the possibility of **emergent behavior**, that is of predicting outcomes which are not "hard wired" into the model. Simple examples of emergent behavior of relevance to this discussion might include the generation of single-parent households by a demographic simulator as a result of more fundamental processes dealing with fertility and household formation and dissolution, or the prediction of unexpected activity/travel patterns by an activity-based model as a result of the occurrence within the simulation of certain combinations of household needs, constraints, etc.

The importance of emergent behavior within travel demand forecasting is at least two-fold. First, it offers the potential for the development of parsimonious models in the sense that relatively simple (but fundamental) rules of behavior can generate very complex behavior. Second, while all models are to at least some degree "captive" to past behavior through use of historical data to estimate model parameters, the potential for emergent behavior increases the likelihood of the model generating unanticipated outcomes, and hence for "departures from the trend" to occur.

Finally, it may well be the case that microsimulation models will ultimately prove easier to explain or to "sell" to decision-makers relative to more aggregate models. Since microsimulation models are

[7] See, for example, Wilson and Pownall [1976].

[8] Ingram, G.K., *et. al.* [1972].

[9] Birch, *et. al.* [1974].

[10] Conversely, many current commercial travel demand modeling software packages require one to work within a matrix-based data structures -- a restriction which can become more and more inconvenient not to mention computationally burdensome, as one attempts to implement more "behaviorally oriented" procedures within them.

formulated at the level of individual actors (workers, home-owners, parents, etc.), relatively clear and simple “stories” can be told concerning what the model is trying to accomplish (e.g., the model estimates the out-of-home activities which a given household will undertake on a typical weekday, and when and where these activities will occur) to which lay people can readily relate. The technical details of the model's implementation typically will be very complex, but the fundamental conceptual design is, in most cases, surprisingly simple to convey to others.

4. POPULATION SYNTHESIS AND UPDATING

Microsimulation models by definition operate on a set of individual actors whose combined simulated behavior define the system state over time. As discussed in Section 2, in short-run forecasting applications, a representative sample may often exist which can define the set of actors whose behavior is to be simulated (Figure 1). In medium- and long-term forecasting applications, however, even if such a sample exists for the base year of the simulation, this sample can not generally be assumed to remain representative over the forecast time period. As discussed in Sections 2 and 3, in such cases the microsimulation model must be extended to include methods for **updating** the attributes of the set of actors so that they continue to be representative at each point of time within the simulation (Figure 2). In addition, in many applications (particularly larger-scale, “general purpose” regional modeling applications), the base year sample of actors either may not be available or may not be suitable for the task at hand. In such cases, the microsimulation model must also include a procedure for **synthesizing** a suitable base year set of actors as input to the dynamic behavioral simulation portion of the model (Figure 3). Each of these two processes — synthesis and updating — are discussed in the following two subsections.

Before discussing synthesis and updating methods, however, one other important model design issue needs to be addressed. The discussion to this point in the paper has assumed that the set of actors being simulated is a **sample** drawn in an appropriate way from the overall population. This is, indeed, the case in most of the microsimulation models developed to date, including the relatively few medium- to longer-term forecasting models reported in the literature, and regardless of whether the base sample is obtained through survey or synthesis methods. Goulias and Kitamura [1992], for example, used sample households from the Dutch Mobility Panel in their microsimulation model of Dutch household demographics and mobility (MIDAS -- Microanalytic Integrated Demographic Accounting System). Mackett [1985, 1990], as another example, used a 1% sample of households synthesized from more aggregate data in his housing market microsimulation model (MASTER -- Micro-Analytical Simulation of Transport, Employment and Residence).

Situations exist, however, in which it may be useful or even necessary to work with the entire **population** of actors within the microsimulation, rather than a representative sample. At least two major reasons exist for why one might prefer to work at the population level rather than with a sample.

First, situations exist in which computing population totals based on weighted sample results can be difficult to do properly.[11] Consider, for example, the problem of simulating residential mobility. Assume that one is working with a 5% sample of households. Then, on average, each household in the sample will carry a "weight" of 20 in terms of its contribution to the calculation of population totals. If it is determined within the simulation that a given sample household will move from its current zone of residence i to another zone j, does this imply that 20 identical households make the same move? The answer is, probably not. More complex weighting schemes can undoubtedly be devised, but it may prove to be conceptually simpler, more accurate and perhaps even computationally more efficient to deal directly with the residential mobility decisions of **every** household and thereby avoid the weighting problem entirely.

All sample-based models inherently represent a form of aggregation in that each observation in the sample "stands for" or "represents" n actual population members (where, as illustrated above, 1/n is the average sample rate). These n population members will possess at least some heterogeneity and hence variability in behavior. In many applications (microsimulation or otherwise) this "aggregation problem" is negligible, and the efficiency in working with a (small) sample of actors rather than the entire population is obvious. In many other applications, such as the one described above, however, use of a sample may introduce aggregation bias into the forecast unless considerable care (and associated additional computational effort) is taken. In such cases, the relative advantages of the two approaches are far less clear.

Second, as one moves from short-run, small-scale, problem-specific applications (the domain of most activity-based simulation models to date) to longer-run, larger-scale, "general purpose" applications (e.g., testing a wide range of policies within a regional planning context -- presumably an eventual goal of at least some activity-based modeling efforts), the definition of what constitutes a "representative" sample becomes more ambiguous. A sample which is well suited to one policy test or application may not be suitable for another. This is particularly the case when one requires adequate representation spatially (typically by place of residence **and** place of work) as well as socio-economically. In such cases, a "sufficiently generalized" sample may be so large and/or sufficiently complex to generate that it might be "just as easy" to work with the entire population.

In trying to build a case for population-based microsimulations, one certainly cannot ignore the computational implications (in terms of both processing time, memory and data storage requirements) of such an approach. This issue is returned to in Section 6. For the moment, the points to note are:

1. the conceptual case for population-based microsimulation does exist, in at least some applications;
2. computing capabilities and costs are continuously improving; and
3. several population-based models are currently under development, the most notable, of course, being the TRANSIMS model [Barrett, *et. al.*, 1995].

[11] As Mackett [1990] observes, these often involve market simulations in which demand-supply interactions are difficult to deal with on a sample basis.

The synthesis and updating methods discussed in the following sub-sections do not depend in any significant conceptual way on whether they are operating on a sample or the entire population. For simplicity of discussion, however, the presentations in these sections assume that it is a disaggregated representation of the entire population which is either being synthesized or updated.

4.1 Population Synthesis

All population synthesis methods start with the basic assumption that reliable aggregate information concerning the base year population is available, generally from census data. These data typically come in the form of one-, two- or possibly multi-way tables, as illustrated in Figure 4. Collectively, these tables define the marginal distributions of each attribute of the population of interest (age, sex, income, household size, etc.). In addition any two-way or higher cross tabulations provide information concerning the joint distribution of the variables involved. The full multi-way distribution of the population across the entire set of attributes, however, is not known. The synthesis task, as shown in Figure 4, is to generate a list of individual "population units" (in the case of Figure 4, households) which is statistically consistent with the available aggregate data.

All synthesis procedures developed to date use some form of Monte Carlo simulation to draw a "realization" of the disaggregate population from the aggregate data. At least two general procedures for doing this currently exist. The first appears to have been originally proposed by Wilson and Pownall [1976]. In this method, the marginal and two-way aggregate distributions for a given zone (or census tract) are used sequentially to construct the specific attribute values for a given person (or household, etc.) living in this zone. For example, assume that we are synthesizing households with three attributes, X_1, X_2 and X_3. Also assume that we have the marginal distribution for X_1 (which defines the marginal probabilities $P(X_1=x_1)$ for the various valid values x_1 for this attribute. We also have the joint distributions for X_1 and X_2 and for X_2 and X_3 (which can be used to define the conditional probabilities $P(X_2=x_2|x_1)$ and $P(X_3=x_3|x_2)$. An algorithm for generating specific values (x_{1h}, x_{2h}, x_{3h}) for household h is then:

1. generate a uniform random number u_{1h} on the range [0,1]. Given u_{1h}, determine x_{1h} from the distribution $P(X_1=x_{1h})$;
2. generate a uniform random number u_{h2}. Given x_{1h} and u_{2h}, determine x_{2h} from the distribution $P(X_2=x_{2h}|x_{1h})$; and
3. generate a uniform random number u_{3h}. Given x_{2h} and u_{3h}, determine x_{3h} from the distribution $P(X_3=x_{3h}|x_{2h})$.

This process is then repeated until all households, each with a specific set of attributes, have been generated.[12] This procedure is conceptually straightforward, easy to implement, and has been used in

[12] Wilson and Pownall proposed this algorithm for the case of generating a small sample. In this case "sampling with replacement" (as occurs in the algorithm outlined) is acceptable. If an entire population set is to be

several models, including Mackett [1985, 1990] and Miller, *et. al.* [1987].

As Wilson and Pownall note, this process implies a causal structure in terms of the order in which the conditional probabilities are computed (i.e., in the assumptions concerning which attributes are conditional upon which others). In practical applications it is not always clear to what extent this conditioning is guided by theoretical considerations as opposed to the availability of a given set of cross tabulations. Alternatively, sufficient redundancy often exists within available census tables that “multiple paths” through these tables may exist, leaving it to the modeler to determine which path is “best” for computing the joint attribute sets (e.g., perhaps one has two-way tabulations of X_1 by X_3 as well as the other two-way tabulations previously assumed; in such a case, which order of conditioning is best?).

More fundamentally, this procedure ignores the potential for significant multi-way correlations among the variables, except for the very limited two-way correlations permitted within the arbitrarily assumed conditional probability structure. This is a potentially serious problem. A recently proposed procedure by Beckman, *et. al.* [1995] for use in TRANSIMS, however, directly addresses this issue.

The TRANSIMS procedure also starts with aggregate census tabulations for each census tract. In addition, however, it utilizes Public Use Microdata Sample (PUMS) files which consist of 5% representative samples of “almost complete” census records for collections of census tracts. Adding up the records in a PUMS provides an estimate of the full multi-way distribution across all attributes for the collection of census tracts. If one assumes that each census tract has the same correlation structure as its associated PUMS, then the PUMS multi-way distribution provides important additional information to the synthesis process. Skipping over a number of important details, primary steps in the TRANSIMS procedure are:

1. For each Public Use Micro Area (PUMA) construct the multi-way distribution of attributes from the corresponding PUMS.
2. A two-step iterative proportional fitting (IPF) procedure is used to estimate simultaneously the multi-way distributions for each census tract within a PUMA, such that each distribution satisfies the marginal distributions for the census tract (as defined by aggregate census tables) **and** has the same overall correlation structure as the PUMS-based multi-way distribution. This IPF procedure can be interpreted as the constrained maximum entropy estimate of the multi-way distribution given the known information and the available PUMS data.
3. Individual households are then randomly drawn **from the full multi-way distribution** for each census tract.

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generated, then the algorithm shown must be altered so that it involves “sampling without replacement”. That is, after each household is drawn, the aggregate household distributions should be modified to reflect the fact that this household has been removed from the distribution, thereby altering slightly the probability distributions for subsequent households.

The TRANSIMS procedure is relatively straightforward to implement and appears to perform well in validation tests to date [Beckman, *et. al.*, 1995]. In particular, it clearly performs better than either drawing households directly from the PUMS multi-way distribution (i.e., without "filtering" this distribution through the census tract marginal distributions by means of the two-step IPF procedure) **or** drawing households directly from the tract marginals (i.e., a simplified version of the Wilson and Pownall procedure). While more operational experience is obviously required with population synthesis methods, the general thrust exemplified by the TRANSIMS approach appears to be well founded: use a "full information" approach which accounts for multi-way correlation among the attributes being synthesized.

4.2 Population Updating

Once the base year population has been provided to the model, either through a survey sample or a synthesis procedure, this population must be "updated" each time step within the simulation run. The nature of this updating obviously depends on the attributes involved, the processes being simulated, the size of the simulation time step, etc. Assuming, however, that one is simulating household processes over a number of years, in one year time steps, demographic and socio-economic processes which need simulating as part of the updating process may well include:

- aging;
- births and deaths;
- marriages and divorces;[13]
- other changes in household structure (adult children leaving the home, etc.);
- non-family household formation and dissolution;
- changes in education level;
- changes in employment status (entry/exit to/from the labor market, change in job location and/or type, etc.);
- changes in residential location;
- changes in automobile holdings (types and numbers of vehicles); etc.

With the exception of aging, which is a completely deterministic accounting process, each of these processes require a sub-model of some sort. Demographic and household structure attributes are generally handled using very simple probability models: either fixed transition rates based on empirical data (e.g., fertility rates for women by age group), or simple parametric probability functions (e.g., MIDAS uses simple logit models to determine household type transition probabilities). In all such cases, Monte Carlo simulation methods are used to generate household-specific "events" (birth of a child, etc.) on a household-by-household and year by year basis.

[13] Generally these terms are used to represent the more generic processes of "couples" forming and dissolving, whether or not actual marriages and divorces occur.

Treatment of employment status, residential location and automobile holdings varies far more widely across models, depending on their application. Each of these can be a significant part (or even the primary focus) of the behavioral modeling component of the microsimulation (see Section 5). Alternatively, if the application permits, one or more of these might be handled in terms of "transition probabilities" in the same way as the demographic variables discussed above.

As with synthesizing procedures, limited experience exists, at least within the travel demand forecasting community, with demographic/socio-economic updating methods. For examples of specific methods used to date, see, Miller, *et. al.* [1987], Kitamura and Goulias [1991], Goulias and Kitamura [1992], and Oskamp [1995]. All of these examples should, I believe, be treated as being illustrative and experimental in nature rather than in any way definitive in terms of "the" method to use. Considerable experience with demographic forecasting obviously exists among demographers. Traditional demographic forecasting, however, does not attempt to work at the fine spatial scale required by our travel demand forecasting applications. Our challenge is to adapt existing methods and/or develop new ones which can operate reliably at the census tract/traffic zone level required for travel demand forecasting.

5. EXAMPLE APPLICATIONS

Much of the travel-related microsimulation modeling which has been undertaken to date has occurred in application areas other than activity-based modeling *per se*. These application areas include: auto ownership, residential mobility, and dynamic network assignment. Sub-section 5.1 briefly reviews representative models from these application areas, with emphasis on their relationship to activity/travel demand modeling. Section 5.2 then briefly discusses examples of activity-based microsimulation modeling.

5.1 Miscellaneous Application Areas.

1. Microsimulation of auto ownership. Some of the earliest applications of microsimulation in the transportation field involved dynamic modeling of auto ownership (e.g., Barnard and Hensher [1982] and Daly [1982]). Behavioral modeling of auto ownership has almost always occurred as a "stand alone" activity, outside of the "normal" activity/travel demand modeling process.[14] Within the travel demand modeling process, auto ownership has typically been treated as just one socio-economic "exogenous" input to the demand process. For some purposes this may be adequate, in which case a "transition probability" treatment within a microsimulation modeling system would be adequate. Many current policy issues, however, (notably concerning emissions and energy use) relate in no small way to household decisions concerning the number and types of vehicles which they own, as well as on the interactions between vehicle holdings and (auto) travel demand. Thus, a strong case exists for including explicit models of household automobile choice within the overall travel demand modeling process [Miller and Hassounah, 1993].

[14] MIDAS [Goulias and Kitamura, 1992], discussed below, represents a notable exception in this regard.

2. Microsimulation of housing markets and residential mobility. Many of the microsimulation models developed to date fall into this general category. Early work includes that undertaken by Wegener [1983], Mackett [1985, 1990] and Miller, *et. al.* [1987]. This continues to be an active area for research efforts, including work by Spiekermann and Wegener [1993] and Oskamp [1995].[15]

[15] Work in this area is also proceeding by a collaborative team of Canadian researchers from the University of Toronto, McMaster University, Laval University and the University of Calgary. This project is in a very preliminary stage at time of writing and has yet to publish results.

Given the central role which lifecycle stage and household structure play in determining residential mobility, these models typically deal in detail with population and household synthesis and updating -- issues of considerable importance to activity-based models (and ones which have already been dealt with in Section 4). In addition to the technical issues relating to synthesis and updating already discussed, note that the discussion to this point in the paper has been relatively indifferent to the "unit of analysis" within microsimulation models. In residential mobility modeling it has long been recognized that both households and persons (with the later being further sub-divided into workers, non-workers, etc.) must be maintained within the modeling system, given that some decisions are inherently household-level in nature (e.g., residential choice), while others inherently occur at the level of the individual (e.g., change jobs), with interactions between both levels continuously occurring[16] (e.g., the decision to change jobs may have ramifications for household income levels and hence the suitability/affordability of the current residential location; the decision on whether/where to move may be influenced by the impact which the move would have on commuting times and costs). As a result, such models generally maintain both households and persons (and mappings between the two) as explicit elements of their database. This dual representation presumably will prove useful to activity-based models, both as they move to more household-level formulations and as they become more integrated with residential mobility models within more comprehensive microsimulation frameworks.

In addition, of course, housing market models are intended to forecast medium- to long-term evolution of the spatial distribution of the residential population, another key input into activity-based models. Considerable debate currently exists, particularly within the United States, concerning "land use - transportation interactions", the nature and extent of "induced demand", etc. Development of credible, integrated models of residential (and employment) location processes and activity/travel demand seems to me to be a particularly important step towards investigating the medium- to long-term impact of both land use and transportation system policies and hence towards contributing in a analytically sound way to this extremely important policy debate.

3. Microsimulation of auto route choice and network performance. As mentioned briefly in Section 3, many current and emerging road network assignment procedures are microsimulation-based (e.g., Barrett, *et. al.* [1995], Hu and Mahmassani [1995], Mahmassani, *et. al.* [1994]). A detailed review of these procedures is well beyond the scope of this paper. Three points to note about these models, however, are:

i) As has already been discussed Section 3, the input requirements of these network microsimulation models may in some instances drive the design criteria for activity-based travel forecasting models. TRANSIMS is perhaps the best example of this point, in that the network performance/emissions modeling needs are clearly in this case driving the overall system design.

ii) The "interface" between the activity-based models and the network models generally does not simply consist of the outputs from the one becoming the inputs to the other. Typically,

[16] See, for example, Birch, *et. al.* [1974].

dynamic route assignment procedures simultaneously determine route choice and trip departure time choice (given assumptions about desired arrival times). DYNASMART perhaps best typifies operational capabilities in this regard. Thus, these models "intrude" into at least one component of the activity-based modeling domain: the "micro-scheduling" of trips. Again, this may well have design implications for activity-based models to the extent that they are intended to be integrated with network microsimulation models.

iii) Most current network microsimulation models appear to have been developed with short-run (and, in some cases, real-time) forecasting applications in mind, often specifically relating to ITS applications. Whether these models are well suited for medium- to long-term forecasting applications is, I believe, an unanswered question at this point in time. Issues include the level of detail of network representation often required by these models (e.g., are we able to specify the traffic signal settings and offsets twenty years into the future, as may be required by some models), as well as the match between network model precision (e.g., second by second calculations of individual vehicles' performance) and the accuracy of the activity/travel demand model's predictions (even with microsimulation!), given the inevitable uncertainties associated with medium- to long-term forecasting.

5.2 Activity-Based Microsimulation Models

Given the inherently disaggregate nature of activity-based models, as well as the fact that these models typically incorporate some level of dynamics, one might argue that a large portion of the extensive activity-based modeling literature should be included in this section.[17] This has not been attempted here. Rather emphasis has been placed on including models which emphasize the connection between activity modeling and travel demand forecasting in at least a quasi-operational manner, and which do this within an explicit microsimulation framework.

Bonsall [1982] provides a very early example of the application of microsimulation to the problem of predicting commuters' participation in a proposed ridesharing program. Although very specialized in nature, the model is noteworthy given its time period of development, as well as for the clarity with which the paper discusses general issues of microsimulation modeling.

Axhausen [1990] reports on a considerable "tradition" in Germany of activity-based microsimulation modeling of destination and mode choice, tracing back to Kreibich's initial work in the late 1970's [Kreibich, 1978, 1979]. Much of this German work has been generally inaccessible to North American audiences since, with the exception of Kreibich's papers, most of it has only been published in German. Axhausen's contribution was to combine an activity chain simulation model (which had been the focus

[17] Very explicitly simulation-based activity-based models such as STARCHILD [Recker, *et. al.*, 1986a, 1986b] and the simulation model developed by Ettema, *et. al.* [1993] particularly come to mind.

of the work of Kreibich, *et. al.*) with a mesoscopic traffic flow simulator.[18] This paper is noteworthy in at least two respects. First, it represents an early attempt to link an activity-based model directly to a network assignment model -- clearly an essential step in developing a true activity-based travel demand forecasting capability. Second, the decision to use a mesoscopic rather than microscopic traffic simulator provides a useful counterpoint to the general North American trend of leaping directly to the extreme micro level for this later type of model.

MIDAS (Microanalytic Integrated Demographic Accounting System) [Kitamura and Goulias, 1991; Goulias and Kitamura, 1992, 1996] represents an extremely important milestone in the development of transportation-related microsimulation models. Developed for the Dutch government, MIDAS is an operational microsimulation-based forecasting tool. Starting with a nationwide sample of households obtained from the Dutch Mobility Panel, the model has two main components: a socio-economic and demographic component which simulates household transitions, including births, deaths, household type changes, as well as changes in persons' employment status, personal income, driver's licence possession and education; and a "mobility component" which simulates auto ownership, trip generation and modal split. Although the application is somewhat atypical (i.e., predicting overall national travel levels rather than intra-urban trip-making), the model contains most of the attributes of the activity-based travel forecasting microsimulation modeling "paradigm" presented in Section 2 of this paper. In particular, the model's treatment of the demographic and socio-economic updating problem is very strong.

In 1992 FHWA commissioned four groups (RDC, Inc., Caliper Corporation, MIT, and the Louisiana Transportation Research Center — LTRC) to propose new modeling systems to replace the conventional four-stage system. It is noteworthy that two of the four groups (RDC and LTRC) proposed activity-based microsimulation designs, while a third (MIT) proposed a disaggregate activity-based approach which certainly could be implemented within a microsimulation framework [Spear, 1994]. Further, both RDC's SAMS (Sequenced Activity-Mobility System) and LTRC's SMART (Simulation Model for Activities, Resources and Travel) postulated an integrated, comprehensive modeling system beginning with land use and flowing through activity/travel decisions to dynamic assignment of vehicles to networks (and hence calculation of congestion, emissions, etc.).

Since the FHWA study, a prototype of AMOS (Activity-Mobility Simulator), the central component of the proposed SAMS system, has been developed and used in Washington, D.C. to evaluate alternative TDM strategies [RDC, 1995]. Within the context of this paper, AMOS represents an example of an activity-based travel microsimulator. As currently implemented, it represents a stand-alone tool for analyzing a specific type of short-run transportation policies which is not currently tied to either a demographic simulator (as in the case of MIDAS) or a network simulator (as in the case of Axhausen's model). More generally, however, it represents a potential stepping-stone towards a more comprehensive microsimulation system such as SAMS which would include these other microsimulation

[18] Mesoscopic network models generally work at the level of the individual vehicle, but make use of much more simplified models of vehicle performance than the microscopic models discussed above. For a detailed discussion of the potential merits of mescopic models, see Miller and Hassounah [1993].

components, among others.

Finally, TRANSIMS [Barrett, *et. al.*, 1995] represents by far the most ambitious attempt to date to develop a comprehensive microsimulation travel demand forecasting model. The TRANSIMS program is well documented in the literature, as well as in other presentations at this conference, and so no attempt will be made in this paper to provide a complete description of the model. From the point of view of this paper it is perhaps sufficient to observe that the TRANSIMS work is at the present time both defining much of the state-of-the-art in microsimulation modeling and challenging other researchers to develop their own thoughts and models. Regardless of the extent to which TRANSIMS *per se* ever becomes an operational planning model, the impetus which it has provided to the development of microsimulation models and to the evolution of travel demand modeling in general is of considerable importance.

6. RESEARCH & DEVELOPMENT ISSUES AND DIRECTIONS

With the exception of MIDAS (and, possibly, AMOS), virtually all travel demand-related microsimulation models developed to date must be classed as "prototypes", designed to demonstrate the feasibility of microsimulation and/or to investigate very specific policy questions. Moving microsimulation "out of the laboratory" and into operational practice will require considerable additional research and development. Some of the key issues, in my opinion, which need to be addressed in this R&D effort include the following.

1. Continued development and testing of population synthesizing and updating methods. Just as conventional four-stage models depend fundamentally on the population and employment inputs provided to them, so the microsimulation systems envisioned within this paper depend on the population demographic and socio-economic "inputs" to the behavioral components of the model. While the TRANSIMS procedure for population synthesis appears very attractive (and emerges out of at least twenty years of experience in the literature with related but simpler methods), clearly much more operational experience is required before such a method can be considered a proven tool. Updating methods similarly have clearly been demonstrated to be feasible but require much further incremental experimentation, improvement and "optimization".

2. Determination of appropriate levels of aggregation. Even in a microsimulation model, aggregation inevitably occurs. Aggregation can occur in space (typically through the use of zones as the spatial unit of analysis, even when modeling individual decision-makers within these zones), time (primarily in terms of the time step used to move the model through simulated time: a model which operates on a one-year time step is temporally more aggregate than one which steps through time on a month by month basis), attributes (no matter how detailed the model's description of an individual, there is always some point beyond which two individuals will be considered "identical"; individuals are, however, exactly that, and by treating them as identical we are, in fact, introducing some amount of aggregation into the analysis[19]), and behavior (e.g., perhaps in a given model all types of non-grocery shopping — everything from buying shoes to buying a new car — might be aggregated into a single activity category).

A major rationale for the disaggregate modeling approach is the minimization of aggregation bias. In the theoretical development of our disaggregate models it is often easy to pretend that these models truly operate at the level of unique individuals acting within their actual individual choice contexts. It must be recognized, however, that **any** operational model will inevitably reach some finite limit of disaggregation (where this limit may be defined by data availability, theoretical insight, methodological capabilities, computational feasibility, and/or application requirements), beyond which aggregate "homogeneity" assumptions are inevitably required. This is neither good nor bad, but rather simply a fact of model building. The key point is to recognize this fact and to make intelligent decisions concerning where finer levels of disaggregation are both **required** and **achievable**, and where more "aggregate" representations either can be used because of the nature of the problem (relative homogeneity does exist, system state estimates are robust with respect to this component of the model, etc.) and/or must be used due to inherent limitations in our modeling capabilities.

Over and above a general concern with finding appropriate levels of disaggregation in our microsimulations, specific issues include:

i) **Treatment of space.** Many activity-based models developed to date are surprisingly "aspatial". If such models are to be practical travel demand forecasting tools they must ultimately be able to generate auto, transit, walk, etc. trips from point to point in space. Or is it zone to zone in space? Considerable uncertainty currently exists about what level of spatial disaggregation is required to support forecasting requirements for emissions analysis, etc. Nor is it currently clear what level of spatial disaggregation is likely to be supportable with respect to data and computational capabilities, even given modern Geographic Information Systems (GIS), etc.

ii) **Treatment of time.** Different urban processes operate within very different time frames. Residential and employment location processes operate over periods of years, typically involving brief periods of intense activity (e.g., looking for a new home or job), followed possibly by decades of inactivity. Most demographic process operate on approximately a yearly scale. Activity/travel decisions, however, occur more typically within daily or weekly time frames. Tailpipe emissions from a vehicle depend critically on the second-by-second decisions of the vehicle's driver.

Within each of these components of the overall travel demand process decisions need to be made concerning the best time step to use in modeling the given component. Is second-by-second simulation of vehicle performance really necessary or can a longer time step (say 5 seconds) be used? Is the day or the week the "fundamental" step in

[19] Section 4 discussed this same issue in terms of the use of a sample of individuals, in which case each sampled individual inevitably ends up represented an aggregate group of "similar" individuals within the model.

modeling household activity and travel dynamics (or is hour-by-hour or minute-by-minute simulation required)? Can one year time steps by used to simulate residential mobility decisions (and if so, how does one handle the "microdynamics" of the housing search process which typically occurs over a period of a few weeks or, at most, months)?

These questions become even more problematical as one attempts to bring these model components into a comprehensive modeling system. It is easy to speak about the need for integrated land use - transportation models, for example, but how does one actually integrate these models, given their very different time frames?

iii) **Selection of attributes.** Models vary in terms of the definition and detail of the attributes of persons, households, etc. being modeled. Decisions concerning these attributes obviously affect, among other components of the model, the nature of the population synthesis and updating procedures required to generate and update these attributes over time. Tradeoffs may well often occur between the ability of the synthesis/updating procedures to reliably provide a given attribute and the relative importance of the attribute within the behavioral model.

3. Linkages among model components. As has been mentioned at various points throughout this paper, linkages between location choice, activity/travel decisions and network assignment and performance models represent both a trend and a desirable feature in microsimulation model development. In particular, analysis of the full range of possible impacts of a given policy may often require a relatively comprehensive modeling system, given the wide range of possible short-run and long-run responses available to individuals and households in many cases.

While conceptually attractive, comprehensive microsimulation models obviously bring with them a host of model design issues, not the least of which is the computational feasibility of such models. It is to be expected that many modelers will continue to develop individual models for various components of the overall process, both as a means for best making progress in the development of these components, and as a means for analyzing problems directly addressable by such models. At the same time, other modelers will continue with the task of developing comprehensive modeling systems, often with simplified versions of the current state-of-the-art component models. Both types of activities obviously are mutually reinforcing and are to be encouraged.

4. Demonstration of the statistical properties of microsimulation models. Almost all microsimulation models include stochastic elements. Surprisingly little attention seems to have been paid to the statistical properties of these models.[20] This may partially be due to the preliminary nature of most models: when one is busy trying to show that the thing simply works at all one may be forgiven for not worrying what the average outcome of a hundred replications of the same model run might look like.

[20] Axhausen [1990] is one of the few authors who spends more than a sentence or so on the issue. Many do not raise the issue at all.

It may also reflect a reluctance on the part of modelers to come to grips with the issue, given both the magnitude of the computational effort to generate a single model run and the complexity of the outcome of the simulation experiment -- i.e., a massively multi-dimensional data structure defining the final system state.

Come to grips with this issue, however, we must, for the output of any single run of a stochastic model is simply one random "draw" from the unknown distribution of possible outcomes. The representatives of this single outcome (and hence its usefulness for planning purposes) is also by definition unknown. In "classical" stochastic simulations, this problem is resolved by executing many replications of the run, each one of which generates additional information concerning the underlying unknown distribution of outcomes. This process continues until one has generated a sufficient number of observations to be able to say statistically meaningful things about the distribution of possible outcomes -- in particular to provide reliable estimates of the means and variances of the final system state.

Much work is required to address this issue in the case of activity-based travel demand microsimulation models. Considerable experimentation is needed to determine the statistical properties of both individual model components and of overall modeling systems — in particular to develop guidelines concerning when replications need to be undertaken and, if performed, how many are generally required. As Axhausen [1990] points out, many standard methods exist for reducing internal variation within simulation model runs, and the usefulness and appropriateness of using such methods must be investigated. Finally, thought must be given to how one does "average" over a set of simulated outcomes in cases of such complexity and high dimensionality as are typical of our applications.

5. Demonstration of computational feasibility. One should never make the mistake of underestimating the computational intensity of microsimulation models. In addition to requiring considerable amounts of CPU time, the memory and disk storage requirements of a large microsimulation model are enormous. Early microsimulation models quickly bumped up against computational limits and/or made significant design comprises in order to maintain computational feasibility. With continuing rapid expansion of the computing power cost-effectively available to both researchers and planners, the definition of what is computationally feasible is being upgraded almost daily. Indeed, the fact that this paper is being presented at this conference is due almost entirely to the extraordinary computing power which is now routinely available to us (relative to even a few years ago), as well as to the universally held expectation that this trend of increasing computing power will continue into the foreseeable future.

Nevertheless, the computational challenges associated with large-scale microsimulations are significant, to say the least. This is particularly the case for population-based (as opposed to sample-based) models. The magnitude of the problem also grows as we move towards more integrated, comprehensive models (e.g., combined models of residential and employment location choice, activity/travel and network assignment).

Ultimately, all of the issues discussed above come together and interact with the issue of computational feasibility in a classic engineering design problem involving tradeoffs between "cost" and "performance".

Every increase in model disaggregation, every extension of its comprehensiveness, every improvement in its statistical reliability comes at a cost in computer time, memory and storage. Conversely, at any point in time, current computational capabilities establish upper bounds in terms of what is cost-effectively doable within the model.

One can think of disaggregation level, extent of comprehensiveness, statistical reliability and computational requirements (among undoubtedly others) as fundamental attributes or dimensions of microsimulation model design. We have only become to explore the design "space" defined by these dimensions. At this point in time we have only the faintest notions of where feasible regions lie within this space, let alone where "optimal operating points" might be found.

Above all else, what is required is considerably more experience in building and using such models. The TRANSIMS project is providing invaluable experience in this regard, but we should not be counting on any one project to provide all the answers. The more experience which is gained by more people in more applications within more computing environments, the better our models will ultimately be — and the more likely it will be that we will end up developing the models which we actually need and can use. In any modeling application, a certain amount of "empirical wisdom" is required before the model can be reliably applied. Such empirical wisdom can only be achieved through doing: by trying, by failing, by experimenting, and, throughout the process by learning and thereby eventually (hopefully) succeeding.

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REFERENCES

Axhausen, K. [1990] "A Simultaneous Simulation of Activity Chains and Traffic Flow", in Jones, P. (ed.) *Developments in Dynamic and Activity-Based Approaches to Travel Analysis*, Aldershot: Avebury, pp. 206-225.

Barrett, C. , K. Berkbigler, L. Smith, V. Loose, R. Beckman, J. Davis, D. Roberts and M. Williams [1995] *An Operational Description of TRANSIMS*, LA-UR-95-2393, Los Alamos, New Mexico: Los Alamos National Laboratory.

Beckman, R.J., K.A. Baggerly and M.D. McKay [1995] "Creating Synthetic Baseline Populations", paper submitted to *Transportation Research*, LA-UR-95-1985, Los Alamos, New Mexico: Los Alamos National Laboratory.

Birch, D., R. Atkinson, S. Sandstrom and L. Stack [1974] *The New Haven Laboratory: A Test-Bed for Planning*, Lexington, Mass.: Lexington Books.

Bonsall, P.W. [1982] "Microsimulation: Its Application to Car Sharing, *Transportation Research A*, Vol. 15, pp. 421-429.

Clarke, M.C., Keys, P. and Williams H.C.W.L. [1980] "Micro-analysis and Simulation of Socio-Economic Systems: Progress and Prospects", in Bennett, R.J. and N. Wrigely (eds.)

Quantitative Geography in Britain: Retrospect and Prospect, London: Routledge and Kegan Paul.

Clarke, M.C., Keys, P. and Williams H.C.W.L. [1981] "Microsimulation in Socio-Economic and Public Policy Analysis" in Voogd, H. (ed.) *Strategic Planning in a Dynamic Society*, Delft: Delftsche Uitgevers Maatschappij BV, pp. 115-125.

Ettema, D., A. Borgers and H. Timmermans [1993] "Simulation Model of Activity Scheduling Behavior", *Transportation Research Record 1413*, pp. 1-11.

Goulias, K.G. and R. Kitamura [1992] "Travel Demand Forecasting with Dynamic Microsimulation", *Transportation Research Record 1357*, pp. 8-17.

Goulias, K.G. and R. Kitamura [1996] "A Dynamic Model System for Regional Travel Demand Forecasting", chapter 13 in Golob, T., R. Kitamura and L. Long (eds.) *Panels for Transportation Planning: Methods and Applications*, Kluwer Academic Publishers, forthcoming.

Hu, T.Y. and H.S. Mahmassani [1995] "Evolution of Network Flows under Real-Time Information: Day-to-Day Dynamic Simulation Assignment Framework", *Transportation Research Record 1493*, pp. 46-56.

Ingram, G.K., J.F. Kain and J.R. Ginn [1972] *The Detroit Prototype of the NBER Urban Simulation Model*, New York: National Bureau of Economic Research.

Kitamura, R. and K.G. Goulias [1991] *MIDAS: A Travel Demand Forecasting Tool Based on a Dynamic Model System of Household Demographics and Mobility*, Project bureau Integrale Verkeer-en Vervoerstudies, Ministerie van Verkeer en Waterstaat, the Netherlands.

Kreibich, V. [1978] "The Successful Transportation System and the Regional Planning Problem: An Evaluation of the Munich Rapid Transit System in the Context of Urban and Regional Planning Policy", *Transportation*, Vol. 7, pp. 137-145.

Kreibich, V. [1979] "Modeling Car Availability, Modal Split and Trip Distribution by Monte-Carlo Simulation: A Short Way to Integrated Models", *Transportation*, Vol. 8, pp. 153-166.

Mackett, R.L. [1985] "Micro-analytical Simulation of Locational and Travel Behaviour", *Proceedings PTRC Summer Annual Meeting*, Seminar L: Transportation Planning Methods, London: PTRC, pp. 175-188.

Mackett, R.L. [1990] "Exploratory Analysis of Long-Term Travel Demand and Policy Impacts Using Micro-Analytical Simulation", in Jones, P. (ed.) *Developments in Dynamic and Activity-Based Approaches to Travel Analysis*, Aldershot: Avebury, pp. 384-405.

Mahmassani, H.S., T.Y. Hu and S. Peeta [1994] "Microsimulation-Based Procedures for Dynamic Network Traffic Assignment", *Proceedings of the 22nd European Transport Forum, PTRC, Seminar H: Transportation Planning Methods: Volume II*, pp. 53-64.

Miller, E.J., P.J. Noehammer and D.R. Ross [1987] "A Micro-Simulation Model of Residential Mobility", *Proceedings of the International Symposium on Transport, Communications and Urban Form, Volume 2: Analytical Techniques and Case Studies*, pp. 217-234.

Miller, E.J. and M.I. Hassounah [1993] *Quantitative Analysis of Urban Transportation Energy Use and Emissions: Phase I Final Report*, report submitted to Energy, Mines and Resources Canada, Toronto: Joint Program in Transportation, University of Toronto.

Oskamp, A. "LocSim: A Microsimulation Approach to Household and Housing Market Modelling", paper presented to the 1995 Annual Meeting of the American Association of Geographers, Chicago, March 15-18, PDOD Paper No. 29, Amsterdam: Department of Planning and Demography, AME - Amsterdam Study Centre for the Metropolitan Environment, University of Amsterdam.

RDC, Inc. [1995] *Activity-Based Modeling System for Travel Demand Forecasting*, DOT-T-96-02, Washington, D.C.: U.S. Department of Transportation.

Recker, W.W., M.G. McNally and G.S. Root [1986a] "A Model of Complex Travel Behavior: Part I -- Theoretical Development", *Transportation Research A*, Vol. 20A, No. 4, pp. 307-318.

Recker, W.W., M.G. McNally and G.S. Root [1986b] "A Model of Complex Travel Behavior: Part I -- An Operational Model", *Transportation Research A*, Vol. 20A, No. 4, pp. 319-330.

Spear, B.D. [1994] *New Approaches to Travel Demand Forecasting Models, A Synthesis of Four Research Reports*, DOT-T-94-15, Washington, D.C.: U.S. Department of Transportation.

Spiekermann, K. and M. Wegener [1993] "Microsimulation and GIS: Prospects and First Experience", paper presented at the Third International Conference on Computers in Urban Planning and Urban Management, Atlanta, Georgia, July 23-25.

Wegener, M. [1983] *The Dortmund Housing Market Model: A Monte Carlo Simulation of a Regional Housing Market*, Arbeits Paper Number 7, Institut fuer Raumplanung, Universitaet Dortmund, Dortmund.

Wilson, A.G. and C.E. Pownall [1976] "A New Representation of the Urban System for Modelling and for the Study of Micro-level Interdependence", *Area*, Vol. 8, pp. 246-254.

Van Aerde, M. and S. Yager [1988a], "Dynamic Integrated Freeway/Traffic Signal Networks: Problems and Proposed Solutions", *Transportation Research A*, Vol. 22A, No. 6, pp. 435-443.

Van Aerde, M. and S. Yager [1988b], "Dynamic Integrated Freeway/Traffic Signal Networks: A Routing-Based Modeling Approach", *Transportation Research A*, Vol. 22A, No. 6, pp. 445-453.